Classification of attention types in EEG signals

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Introduction:

Zomeren and Brouwer led researches on attentional deficits and found the existence of at least four attention domains. Alertness and sustained attentions refer to the intensity of attention (i.e., its strength) whereas selective and divided attentions refer to its selectivity (i.e., the amount of information that are monitored) [14]. The BCI literature has already shown that both some stable attentional capacities of subjects and the fluctuant attentional resources dedicated to the task by the latter are related to MI-BCI performances [8]. Indeed, it was shown that results from attentional tests, such as the digit span, are correlated with MI-BCI performances [3,7]. Furthermore, both spectral (i.e., alpha and theta) and spatial (i.e. attentional networks) neural correlates were correlated with MI-BCI [1,5,6,13]. This study aims at investigating whether we can classify the EEG signatures of the different attention types using EEG, with the future goal to apply this classification to MI-BCI.

Material, Methods and Results:

We asked 16 participants (5 women; mean age= 32,4 y.o.) to perform different tests related to the different types of attention presented in the previous section. During each task, participants had to react as fast as possible -by pressing a keyboard space bar- to the appearance of target stimuli while we recorded their EEG. The tasks and types of attention were differentiated by the type of sensorial modality of the stimuli, number of distractors, presence of a warning before the stimuli and the length of the task. The characteristics of the different tasks were chosen based on the literature [4,10,11,12].

For each attention task, 80 targets stimuli were presented. We only selected the ones that were at least one second apart from a motor response and used one second prior target presentation as analysis window. The subject-specific discriminability of the EEG patterns between each pair of attention tasks was then assessed using Common Spatial Pattern filtering in the alpha range (8-12Hz) and a Linear Discriminant Analysis classifier, with 5-fold cross-validation using the tool described in [2]. Results are promising and range from 83% accuracy (sd=0.09) to discriminate Alertness (Tonic) from Sustained attention (see Figure) to 74% accuracy (sd=0.13) to discriminate Selective and Divided attention. From the topography representing the mean inter-subject differences from t-tests of the Power Spectral Density in alpha range between the Alertness (Tonic) and Sustained attention we distinguish an influence of the temporal brain region which has already by shown in previous studies [9,11].

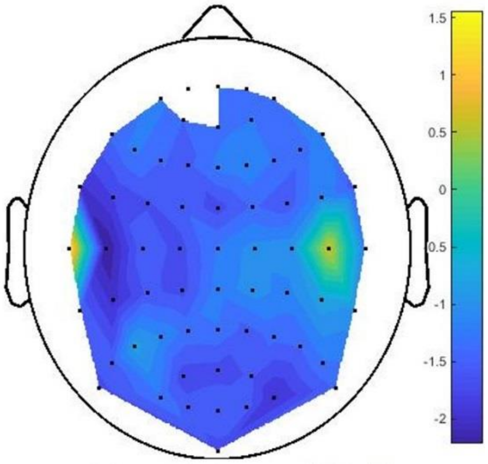

Figure: Intersubject mean PSD differences in alpha range for Alertness (Tonic) vs. Sustained attention

Discussion:

These results tend to validate the model of Zomeren and Brouwer and indicate that the four types of attention from the model are distinguishable from one another. Current work focused on the alpha frequency range because literature indicates that it is both related to attention and MI-BCI performances [13]. We will also explore the characteristics of the types of attention, the influence of other frequency bands as well as the influence of the performance of the subjects (i.e. reaction time, accuracy) on their EEG.

Significance

The literature indicates an influence of attention on MI-BCI performances [7,1] though it would be interesting to test if a feedback related to attention(s) could improve MI-BCI performances. Given the literature it seems that the feedback should focus on selective attention though it would be interesting to test this hypothesis by using the results of this article and classifying the EEG data from someone performing a BCI task.

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References

1. Ahn et al, PloS one, 2013.
2. Appriou et al, BCI meeting, submitted
3. Daum et al, J. Neurol. Neurosur. PS., 1993.
4. Francis, Atten., Percept., & Psychophy., 2010.
5. Grosse-Wentrup, Int. J. Bioelectromagnetism, 2011.
6. Grosse-Wentrup et al, J. Neural Eng., 2012.
7. Hammer et al, J. Biol. Psychol., 2012.
8. Jeunet, Doct. dissert., Bdx Univ., 2016.
9. Nobre et al, Brain: a journal of neurology, 1997.
10. Schmidt, Psychol. bulletin, 1968.
11. Sturm et al, Neuropsych. Rehab., 1997.
12. Van Leeuwen et al, Atten., Percept., & Psychophy., 2004.
13. Zhang et al, Neuroimage, 2016.
14. Zomeren et al, Oxford Univ. Press, 1994.